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A Novel Recent-biased Dimensionality Reduction Framework for Sensor Data Analysis

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Abstract: Current data analysis methods in processing sensor data, does not take into account the different contribution between the new data and the old data for the whole dataset, which fails to reflect the importance of new data. In this paper, a recent-biased dimensionality reduction method is proposed for sensor data analysis, which uses a multilinear dimensionality reduction learning algorithm with forgetting factor introduced. With the proposed dimensionality reduction method, the impact of the new sample data for the future trend of sensor data is highlighted, which can avoid the dilemma of data saturation phenomenon; the sensor data is organized into high order tensor pattern, which keeps the original structure, discriminates information and integrity of the data. Moreover, in order to evaluate the proposed dimensionality reduction method, a new framework of datasets quality assessment is introduced. The experiment results show that, compared with principal component analysis and multilinear principal component analysis, the proposed novel dimensionality reduction method can be more effectively applied to analyzing the sensor data.

Key words: Dimensionality reduction, recent-biased, multilinear subspace learning, sensor network

INTRODUCTION

With the development of sensor technology, sensor nodes are getting smaller and smaller, currently containing thousands, possible millions of nodes in the future (Khedr and Mahmoud, 2012; Tuah *et al*., 2012). Therefore, processing the large amounts of data generated by the sensor network is a serious challenge (Le Borgne *et al*., 2008). High-dimensional data will bring the curse of dimensionality for data mining methods and the amount of data transfer will directly determine the power consumption of the sensor (Younis *et al*., 2012). Therefore, interests have grown in applying data dimensionality reduction technique to the sensor data processing in recent years. According to the specific application, sensor data dimensionality reduction algorithm comprises the unsupervised learning method, such as principal component analysis (Yu *et al*., 2009), Karhunen-Loève transform (He *et al*., 2006), manifold learning (Zhao and Zhang, 2011) and supervised learning method such as discriminant analysis (Sikirzhytski *et al*., 2010), canonical correlation analysis (Nielsen, 2002). Distributed algorithms of these methods also have been proposed in the past few years for sensor networks.

However, with increasing requirements for sensor applications and theoretical study, the data processing and data dimensionality reduction method exposed some deficiency in theory. In fact, many dimensionality reduction and modeling methods take recent data and old data as equally important. With more and more new data collected, the recent changes cannot be well kept when data series become very long, so that the model gradually loses correction ability, which is called as 'data saturation phenomenon' (Phithakkitnukoon and Ratti, 2010). Therefore, different weights are assigned to the samples at different time, which has great significance for processing and analyzing of the sensor data. The above conventional methods of data processing and data dimensionality reduction are nonactionable in solving the dilemma caused by the "data saturation phenomenon".

Besides, many collected sensor data are naturally tensor objects. For example, the images collected from image sensor are three modes tensor objects with column, row and color (Rittner *et al*., 2010). Gait silhouette sequences, as well as grayscale video sequences from video sensor can be viewed as three modes tensors (Lu *et al*., 2008) with column, row and time modes. Data in environmental sensor monitoring is often organized in tensor with three modes of time, location and type. This paper will use multilinear principal component analysis method to deal with the sensor data. Being different from traditional vector learning methods, multilinear principal component analysis is based on the tensor learning, which can take into account the changes in each dimension of the sensor data and can keep the original structure and discrimination information of data in the process of dimensionality reduction.

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The main contribution of this article is to provide a Recent Biased-Multilinear Principal Component Analysis framework (RB-MPCA). The forgetting factor is introduced into the dimensionality reduction process of the sensor data and the samples from different time can be assigned with different weights, which can effectively solve the problem of data saturation. At the same time, considering the characteristics of the sensor data, the future trend of sensor data has a stronger correlation with new samples than the old ones. So giving more weight to the new samples will highlight the impact that new samples contribute to the future trends of the sensor serial data. The experiments performed on two real datasets show that the proposed RB-MPCA is more effective to handle the prediction and decision problem of sensor data.

This study is organized as follows. Section 2 presents the basic multilinear algebra and multilinear subspace learning, which is the basis of the multilinear principal component analysis. Section 3 introduces the proposed RB-MPCA framework. Experiment process and result on two real public sensor datasets are described in this section. The major conclusion of this work and future research tracks are addressed in Section 4.

MULTILINEAR SUBSPACE LEARNING

Multilinear subspace learning built on multilinear algebra is the extension of linear subspace learning. This section first introduces some elementary definitions and conclusions of the multilinear algebra and then the multilinear subspace learning.

Basic multilinear algebra: Some terminologies on tensor operations are given as follows (Lathauwer *et al*., 2000; Lu *et al*., 2008; Lu *et al*., 2011) which are used in the following multilinear subspace learning. Assume N th-order tensor $A,B\in R^{I_1\times I_2\times\cdots\times I_N}$, where $i_n(1\le i_n\le I_n,n=1,\cdots N)$ addresses the each n mode of A. The $(i_1,i_2,\cdots,i_N)$ element of a tensor A is denoted by $A_{i_1,i_2,\ldots,i_N}$.

Definition 1: (Tensor addition and subtraction, scalar product, frobenius-norm) The addition and subtraction of two tensors is given by $(A\pm B)_{i_1,i_2,\cdots,i_N}=A_{i_1,i_2,\cdots,i_N}\pm B_{i_1,i_2,\cdots,i_N}$. The scalar product <A, B> of two tensors A, B is defined as:

$$< A, B >= \sum_{i_1=1}^{I_1}$$

$$\sum_{i_2=1}^{I_2}\cdots\sum_{i_N=1}^{I_N} A_{i_1,i_2,\cdots i_N}\cdot B_{i_1,i_2,\cdots i_N}$$

The Frobenius-norm of a tensor A is given by $\|A\|_F=\sqrt{< A, A >}$.

Definition 2: (Matrix Unfolding or Mode-n Matricizing) The mode-n matrix unfolding $A_{(n)}$ of an tensor A is defined as the matrix whose columns are the $I_{(n)}$-dimensional vectors obtained from A by varying the index $i_{(n)}$ and keeping the other indices fixed.

Definition 3: (Mode-d product) The mode-d product of a tensor A by a matrix $U\in\mathbb{R}^{J_n\times I_d}$ is denoted by $A\times_d U$, which is an $I_1\times I_2\times\cdots I_{n-1}\times J_n\times I_{n+1}\cdots\times I_N$-tensor and the entries are given by:

$$(A\times_d U)_{i_1,\ldots i_{d-1},j_n,i_{d+1},\ldots,i_n}=\sum_{i_d}(A_{i_1,\ldots,i_n}\cdot U_{j_n,i_d})$$

Multilinear subspace analysis: Assuming X is a N th-order tensor in a multilinear space $\mathbb{R}^{I_1\times I_2\times\cdots\times I_N}$, the key problem of multilinear subspace learning is to find a sequence of linear transformation matrices $U^{(i)}\in\mathbb{R}^{I_i\times P_i}(I_i>P_i,1\le i\le N)$, to transform a high-dimensional tensor X to a low-dimensional tensor $Y\in\mathbb{R}^{P_1\times P_2}$. i.e.:

$$Y=X\times_1 U^{(1)^T}\times_2 U^{(2)^T}\times\ldots\times_N U^{(N)^T}$$

Compared with the linear subspace learning, tensor representation can effectively reduce the number of parameters need to be estimated. Considering the transformation from $X\in\mathbb{R}^{I_1\times I_2\times\ldots\times I_N}$ to $Y\in\mathbb{R}^{P_1\times P_2\times\ldots\times P_N}$, linear subspace learning needs estimate:

$$N_1=\prod_{i=1}^{N}I_{ii}\prod_{i=1}^{N}P$$

independent parameters, multilinear subspace learning needs to estimate:

$$N_2=\sum_{i=1}^{N}I_i P_i$$

independent parameters (Tao *et al*., 2007). For example, the dimensionality reduction from tensor $A\in\mathbb{R}^{20\times20\times20}$ to $B\in\mathbb{R}^{10\times8\times4}$, the number of the parameters that need to be estimated is 640000 with linear subspace learning, while only 380 parameters are required to estimate with multilinear subspace learning.

Based on the discussions above, it can be seen that the parameter estimation in linear subspace learning becomes extremely difficult for high-dimensional tensor objects. Furthermore, when dealing with some data such as high-resolution images and video, the computer will be brought into the dilemma of insufficient computing

capability (Lu *et al*., 2011).When the number of samples obtained by the sensor is limited, estimating too many parameters will increase the complexity of the model and may cause over-fitting problems. Multi-linear subspace learning reduces the number of parameters needed to be estimated and is less susceptible to the small sample size problem (Tao *et al*., 2007).

Recent Biased Multilinear Principal Component Analysis: Motivated by the works in (Paleologu *et al*., 2008), which successfully conduct the application in the field of machine learning and system identification by introducing the forgetting factor in optimality criterion, this section introduces a new recent-biased total scatter for tensor objects. The basic idea is keeping more details on recent data and less details on older data. With the characteristics of the data sequence taken into account, more weights are given to the new samples, which highlights the effect on the future trend of the sequence data by new samples. The recent-biased total scatter is defined as follows:

Definition 4: Given a tensor sample set $\{A_m \in \mathbb{R}^{I_1} \otimes \mathbb{R}^{I_2} \ldots \otimes \mathbb{R}^{I_n}, m=1,\ldots,M\}$, where A_m is the latest data and A_1 is the oldest data. Define α $(0<\alpha\leq 1)$ be the recent-biased rate of the tensor set. The total scatter of these tensor is defined as:

$$\Psi_A = \sum_{m=1}^{M} \left\| \alpha^{M-m} (A_m - \overline{A}) \right\|_F^2$$

Where:

$$\overline{A} = 1/M \sum_{m=1}^{M} A_m$$

Based on the total scatter defined above, the mode- total scatter matrix of these samples is then defined as:

$$S_{T_A}^{(n)} = \sum_{m=1}^{M} (A_{m(n)} - \overline{A}_{(n)})\, W_m \cdot (A_{m(n)} - \overline{A}_{(n)})^T$$

where, $W_m = (\alpha^{M-m})^2$ and $A_{m(n)}$ is the mode-n unfolded matrix of A_m.

The Recent-Biased Multilinear Principal Component Analysis of the sequence data can be described as follows:

The multilinear principal component analysis is trying to project the data to the tensor subspace of maximal variances so that the reconstruction error can be minimized. Given a set of tensor samples $\{X_m \in \mathbb{R}^{I_1 \times I_2 \times \ldots \times I_N}, m=1,\ldots,M\}$, assuming the data variance information is determined by the total scatter, the multilinear principal component analysis is solving the projection matrix $\{U^{(n)} \in \mathbb{R}^{I_n \times P_n}, n=1,\ldots,N\}$ to maximize the total scatter.

$$\begin{cases} \{U^{(n)}, n=1,\ldots,N \arg \max_{U^{(1)}, U^{(2)}, \ldots, U^{(N)}} \Psi_y\} \\ \text{s.t.} \quad U_{(n)^T} U^{(n)} = I \end{cases} \tag{1}$$

To solve the optimization problem above, this paper use $\Phi^{(n)}$ to denote the n-mode total scatter matrix of the tensor samples. The following theorem 1 ensures that the $U^{(n)}$ is an orthogonal projection matrix maximizing the total scatter, when all other projection matrix $U^{(1)}$, ..., $U^{(n-1)}$, $U^{(n+1)}$, ..., $U^{(N)}$ are fixed.

Theorem 1: Assuming $\{U^{(n)}, n = 1, \ldots, N\}$ is a solution for (1):

$$\Phi^{(n)} = \sum_{m=1}^{M} \left(((X_{m(n)} - \overline{X}_{(n)}) . U_{\Phi(n)}) . W_m . (U_{\Phi(n)}^T . (X_{m(n)} - \overline{X}_{(n)})^T \right)$$

where, $W_m = (\alpha^{M-m})^2$, $U_{\Phi(n)} = U^{(n+1)} \otimes U^{(n+2)} \otimes \ldots \otimes U^{(N)} \otimes U^{(1)} \otimes U^{(2)} \otimes \ldots \otimes U^{(n-1)}$. When all other projection matrix $U^{(1)}$, ..., $U^{(n-1)}$, $U^{(n+1)}$, ..., $U^{(N)}$ are fixed, $U^{(n)}$ is consist of eigen vectors corresponding to the largest eigen values of $\Phi^{(n)}$.

The proof of this theorem can be derived from (Lu *et al*., 2008). The $U^{(n)}$ can be obtained by solving the eigen-decomposition of n-mode total scatter matrix based on theorem 1. Motivated by the mutilinear subspace learning method in (Lu *et al*., 2008), this paper improves the iterative procedures and proposes the RB-MPCA algorithm:

Step 1: Update the input samples:

$$\{X_m \in \mathbb{R}^{I_1 \times I_2 \times \ldots \times I_N}, m=1,\ldots,M\}$$

Where:

$$\overline{X} = 1/L \sum_{m=1}^{M} X_m$$

is the latest data and is the oldest data

Step 2: Center t $\{\widetilde{X}_m = X_m - \overline{X}, m=1,\ldots,M\}$ he input samples:

Where:

$$\overline{X} = 1/L \sum_{m=1}^{M} X_m$$

is the sample mean

Step 3: Compute the eigen-decomposition of:

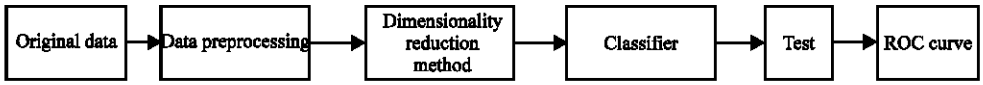

Fig. 1: The block diagram of the comparison of dimensionality reduction methods

$$\Phi^{(n)*} = \sum_{m=1}^{M} \widetilde{X}_{m(n)} \cdot W_m \cdot \widetilde{X}_{m(n)}^{T}$$

initialize $U^{(n)}$ with eigen vector corresponding to the largest eigenvalue

Step 4: Compute $\left\{\widetilde{Y}_m = \widetilde{X}_m \times U^{(1)T} \times U^{(2)T} \ldots \times_N U^{(N)T}, m = 1, \ldots, M\right\}$

-Compute:

$$\Psi_{Y_0} = \sum_{m=1}^{M} \left\|\widetilde{Y}_m\right\|_F^2 \quad m = 1, \ldots, M$$

For t = 1: T_{max}

-For n = 1: N

*Compute the eigen-decomposition of:

$$\Phi^{(n)} = \sum_{m=1}^{M} \widetilde{X}_{m(n)} \cdot U_{\Phi(n)} \cdot W_m \cdot U_{\Phi(n)}^{T} \cdot \widetilde{X}_{m(n)}^{T}$$

update with eigen vector corresponding to the largest eigenvalue, where $U_{\Phi(n)} = U^{(n+1)} \otimes U^{(n+2)} \otimes \ldots \otimes U^{(N)} \otimes U^{(1)} \otimes U^{(2)} \otimes \ldots \otimes U^{(n-1)}$

-Compute:

$$\left\{\widetilde{Y}_m, m = 1, \ldots, M\right\}, \Psi_{Y_t}$$

-IF $\Psi_{Y_t} - \Psi_{Y_{t-1}} < \eta$, break, go to setp 5.

Step 5: Set $\{Y_m = X_m \times_1 U^{(1)T} \times_1 U^{(2)T} \ldots \times_N U^{(N)T}, m = 1, \ldots, M\}$

EXPERIMENT

Two popular real public sensor datasets are used in the following experiments: Intel Lab Dataset from The Intel Berkeley Research Laboratory and Library Sensor database from the Wireless sensor networks lab of Vrije Universiteit Brussel. In order to evaluate the proposed RB-MPCA method, a new datasets quality assessment framework for the comparison of dimensionality reduction methods is introduced.

As depicted in Fig. 1. After data preprocessing, we have these data be normalized. Then we use the PCA, MPCA and RB-MPCA, respectively to obtain the low-dimensional representations of the sample data to form the corresponding dimensionality reduction datasets. Next, four kinds of classifier, Nearest Neighbor Method (Li *et al*., 2011) K-means Clustering Algorithm (Zalik, 2008), K-nearest Neighbor Method (Kudo *et al*., 2003), NeuralNetwork (Doulamis *et al*., 2003) are used to deal with the three dimensionality reduction datasets. Each classifier with the same initial parameters is performed on the three datasets separately. Finally, by adjusting the threshold, we can we can get the Receiver Operating Characteristics (ROC) curves and Area Under the ROC-curve (AUC) values of the classifiers corresponding to the different low-dimensional datasets. Through the comparison of ROC curves and AUC values, those dimensionality reduction methods can be evaluated. Differentiated from traditional evaluation method that only assess the performance of the classifier at a single work point, ROC curve reflects the performance of the classifier in all possible thresholds(Fawcett, 2006). Rather than considering raw error, ROC analysis decomposes performance into true and false positive rates. Therefore, ROC analysis is held to provide a more robust comparative evaluation of expected performance on target data than a simple comparison of errors, which can be used to provide an objective assessment of the observed datasets distribution when the same classifier is used. Through the comparison of the ROC curves and the AUC values, we can analyze the performance of different dimensionality reduction methods.

Intel Berkeley dataset: Intel Berkeley dataset is based on sensor measurements collected at Intel Berkeley Research Laboratory in 2004. The data set contains 2.3 million readings collected from 54 sensors deployed in laboratory for more than a month, which contains humidity, temperature, light and voltage values.The measurements of each sensor are recorded with a unique time ID, which is called epoch number. With this unique number the measurements from different sensors at the same time can be obtained accurately. However, the number of sensors that have corresponding epoch number is much less than 54.Therefore, if all 54 sensor data is retained, we can only get a few samples. In the experiment, we use the data form 8 sensors, numbered 1, 2, 3, 4, 38, 40, 41, 42. If one sensor contains more than one reading at the same time, we use the first readings. After the data preprocessing described above, 70 samples could be obtained. According to the sensor's location, we divided the dataset into two classes and each class has four sensors. The samples in one class at the same time are organized as a tensor in the process of dimensionality reduction. The first 30 data samples are

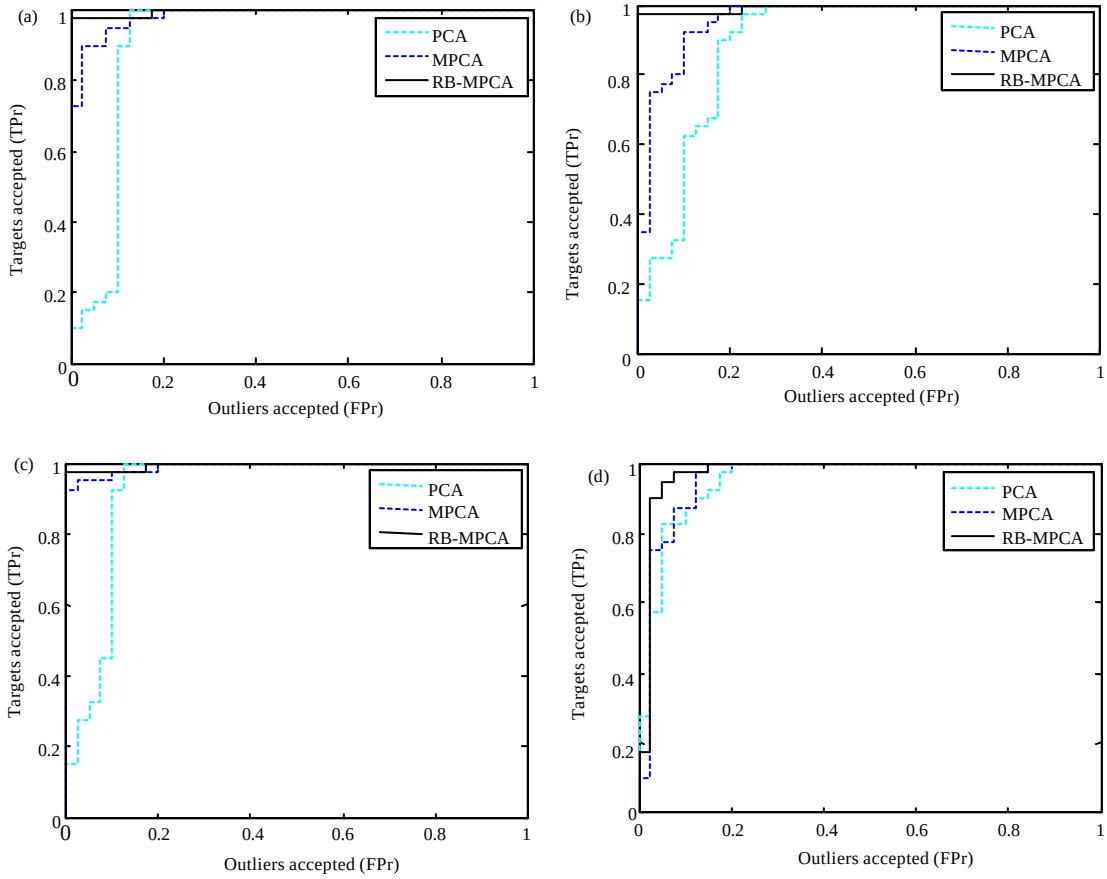

Fig. 2(a-d): ROC curves of four classifiers, (a) Nearest neighbor method, (b) K-means clustering algorithm, (c) K-nearest neighbor method and (d) Neural network

Table 1: The AUC values of four classifiers

	Classifiers			
Dimensionality reduction method	Nearest neighbor	K-means clustering	K-nearest neighbor	Neural network
PCA	0.9131	0.8938	0.9281	0.9544
MPCA	0.9838	0.9612	0.9919	0.9587
RB-MPCA	0.9956	0.9944	0.9956	0.9738

Table 2: The AUC values of four classifiers

	Classifiers			
Dimensionality reduction method	Nearest neighbor	K-means clustering	K-nearest neighbor	Neural network
PCA	0.9706	0.9712	0.9725	0.9400
MPCA	0.9712	0.9775	0.9731	0.9650
RB-MPCA	0.9738	0.9831	0.9762	0.9756

used for training, the remaining 40 data samples as test samples. The recent-biased rate is 0.968. Table 1 is the AUC value of each classifier, Fig. 2 is the ROC curves of the classification results.

Library 1 dataset: Library 1 dataset is collected by wireless sensor networks lab of University of Brussels. The dataset involves 19 TMote Sky sensor nodes distributed in one room, collected within a period of more than 24 h with temperature, humidity and light data. The dataset contains 29702 samples. The same as above, according to the sensor's location, we divided the dataset into two classes. One consists of node 2, 3, 6, 7, the other consists of node 12, 13, 16, 17. The samples in one class at the same time are organized as a tensor in the process of dimensionality reduction. If one sensor contains more than one readings at the same time, we use the mean of these readings. After the data preprocessing described above, 67 samples could be obtained. The first 27 samples are used for the training and the remaining is used for testing. The recent-biased rate is 0.92. Table 2 shows the AUC value of each classifier, Fig. 3 is the ROC curves of four classifiers.

Experiment result: The experiments on Intel Berkeley dataset and the Library 1 dataset show that the AUC

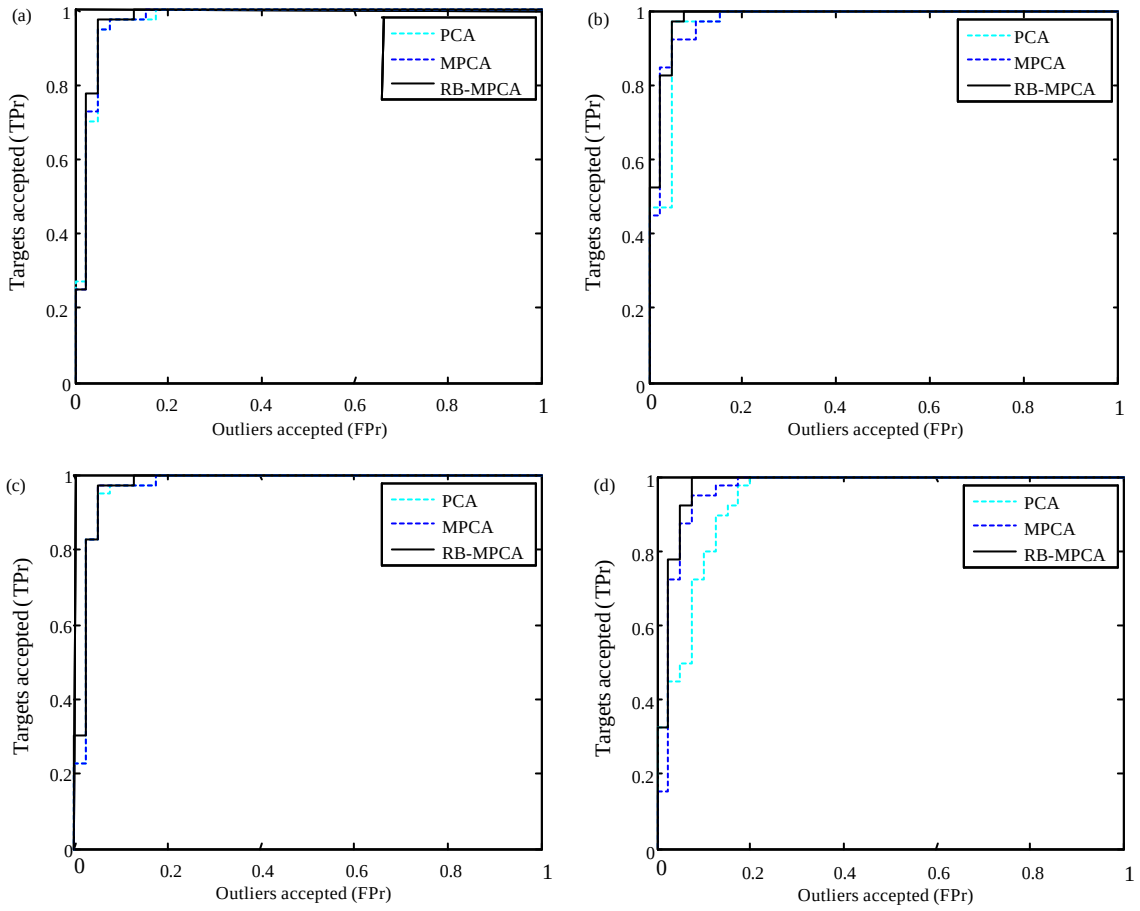

Fig. 3(a-d): ROC curves of four classifiers, (a) Nearest neighbor method, (b) K-means clustering algorithm, (c) K-nearest neighbor method, (d) Neural network

values of four different classifiers using the RB-MPCA dimensionality reduction method are higher than the classifiers using PCA and MPCA method. The AUC value reflects the recognition capacity that the algorithm correctly distinguishes the true and false target (Hand and Till, 2001). For each kind of classifier, using the RB-MPCA dimensionality reduction can achieve a higher AUC values in ROC curve, which indicates that the RB-MPCA algorithm has a better performance than other dimensionality reduction methods.

CONCLUSION

This study proposes a novel recent-biased dimensionality reduction framework for sensor data analysis. The forgetting factor is introduced in the subspace learning of sensor data and the calculation method is given to project the data to the tensor subspace of maximal variances. Unlike many previous sensor data processing methods for sequence data which give the same weight for each sample, our framework highlights the correlation between the new samples and the future trends of data, which makes it more effective to handle prediction and decision problems. The proposed method is tested and verified by performing experiments on two real datasets. The proposed method is not only suitable for environment sensor data, but can also be used for other sensor data, such as image data, video data and so on. Meanwhile, the proposed framework can be treated as a reference to deal with other small sample data of high-dimensional. In this paper, the multi-linear subspace learning algorithm is solved by iteration; in some cases solution precision will affect the recognition performance. Therefore, finding new calculation method for RB-MPCA needs further study, which is expected to have a better ability to handle the dimensionality reduction of complex data.

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